Project ID: EEMS038

JUNE 3, 2020

CHARGING AND REPOSITIONING DECISION MAKING FOR FULLY AUTOMATED RIDE-HAILING FLEET

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2020 DOE Vehicle Technologies Office Annual Merit Review

INL/MIS-20-58134

OVERVIEW

Timeline

- Start: October 2018
- End: September 2019
- 100% Complete

Budget

- FY19: $100K

Barriers

- The influence of fleet management strategies and charging infrastructure availability on automated electric vehicles (AEVs) in ride-hailing fleets is not yet understood
- High risk to develop and deploy advanced vehicles and infrastructure

Partners

- Idaho National Laboratory (INL)

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AEVS PRODUCE MOBILITY CHALLENGES AND OPPORTUNITIES

- AEVs create a new paradigm with capability of driving themselves to charging station after passengers exit
- AEVs in commercial ride-hailing fleets must have the intelligence and awareness to decide when and where to charge, which is a part of an overall fleet management approach

Image Credit: GM Cruise

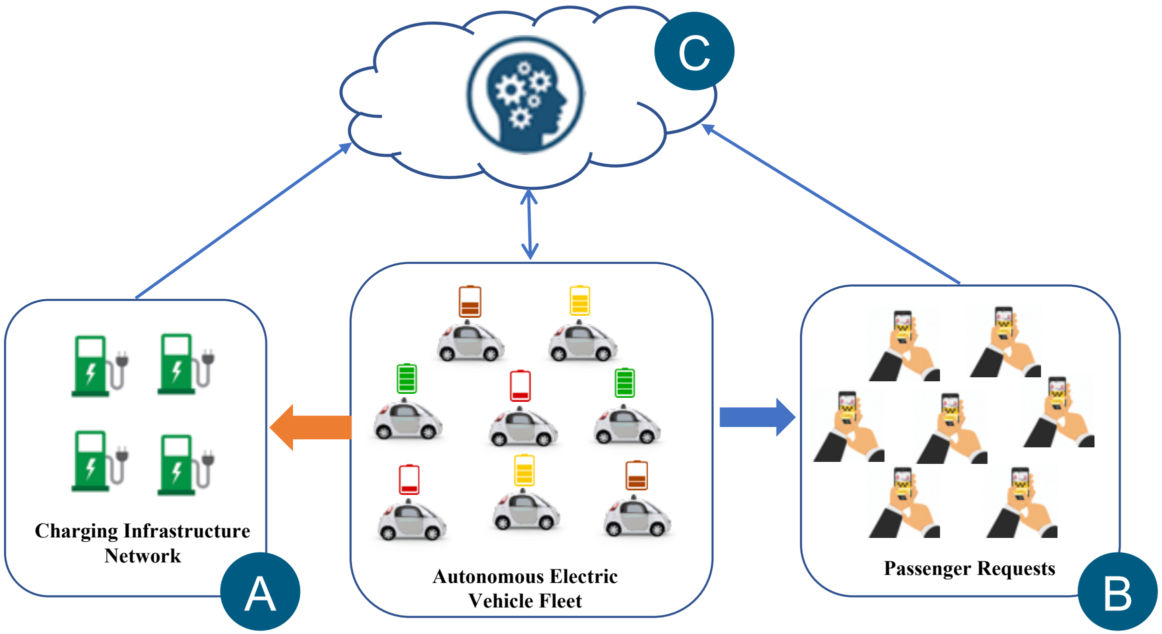
Objective

- Develop heuristic and system-optimization approaches for repositioning and charging decisions for an AEV ride-hailing fleet
- Simulate the operation of a fleet of ride-hailing AEVs in New York City (NYC) using the developed approaches
- Quantify and compare the mobility benefits under the two fleet operation strategies

MILESTONES

Milestone Name/Description	End Date	Status
Incorporate charging decision management strategies and infrastructure scenarios into simulation	6/30/2019	Complete
Complete simulation and publish results comparing the performance of fleet management strategies based on heuristics and optimization	9/30/2019	Complete

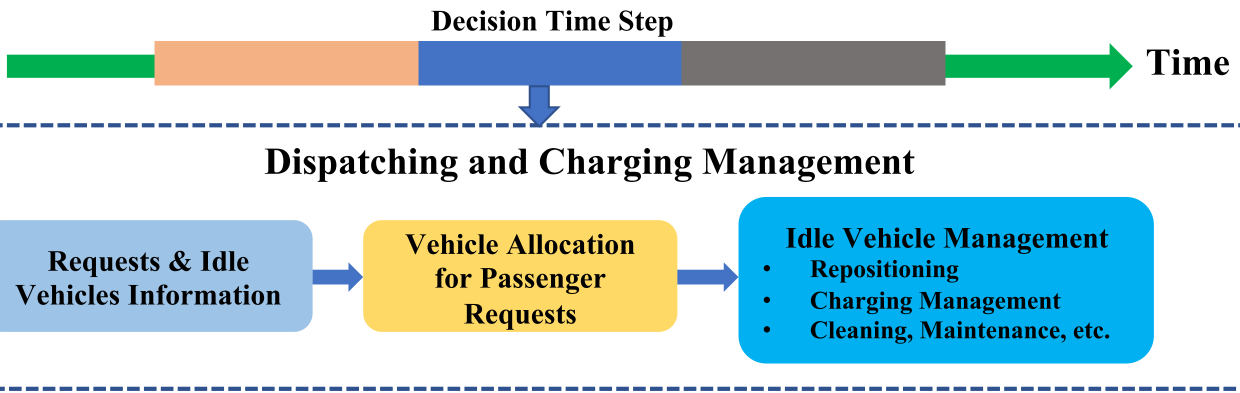
AEV RIDE-HAILING FLEET OPERATION FRAMEWORK



A. Charging infrastructure network compatible with AEVs
B. Ride-hailing travel demand (ride requests) represented by pick-up and drop-off location information and rider's maximum wait time
C. Centralized decision-making framework for dispatching and charging management

DISPATCHING AND CHARGING MANAGEMENT

- Systematic optimization approach considers all vehicles, ride requests, and chargers in the area and applies multiple criteria to choose which vehicles to reposition to which areas and whether and where to charge
- Heuristic approach assumes each vehicle independently decides whether and where to reposition and charge based on heuristic strategy



MECHANISMS OF TWO MANAGEMENT STRATEGIES

Optimization strategy

Balances the following two competing objectives:

1. Minimize passenger's wait time for pick-up to maximize the number of served requests (not served if wait time > 15 min)
2. Minimize the zero-occupancy vehicle (ZOV) miles driven due to traveling to pick up passengers, repositioning to capture the next ride request, or traveling to charge

Heuristic strategy

1. A vehicle with sufficient state of charge(SOC) chooses where to reposition by sampling a probability distribution that is weighted toward the area with ride requests with the longest wait time
2. A vehicle chooses the closest unoccupied charging station if SOC drops below threshold

Performance Metrics

- Zero-occupancy vehicle miles traveled
- Ratio of successfully served ride requests
- Fleet charging downtime
- Utilization rate of charging infrastructure

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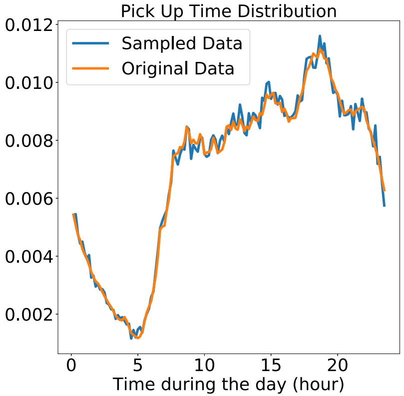
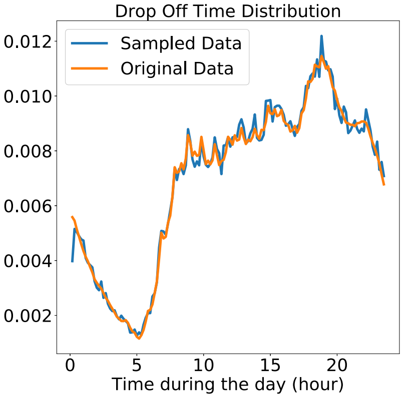
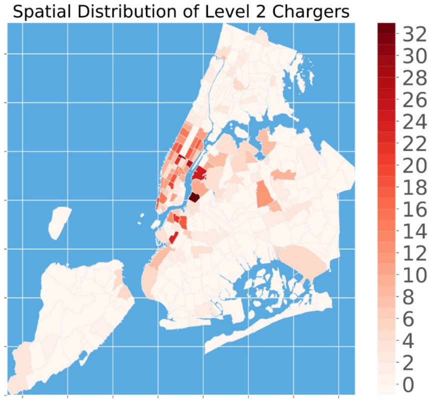
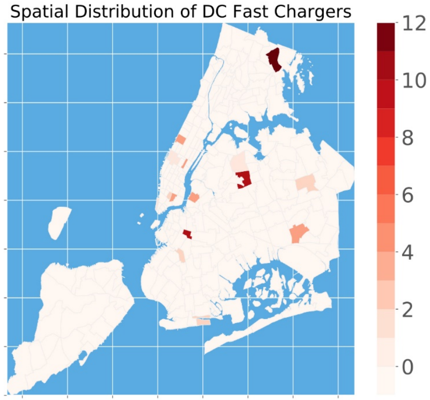
SIMULATION TO DEMONSTRATE FLEET MANAGEMENT STRATEGIES

- 100,000 ride requests each day, sampled from real-world NYC taxi data (approx. 30% of actual daily demand to reduce computation time)
- AEV fleet sizes within the range from 500 to 4,000
- Two options for charging stations:
  1. Today's charging network in NYC with both AC Level 2 and 50-kW DC fast chargers
  2. Use today's charging station locations in NYC, assume all chargers are 50-kW.
- Each run simulated three consecutive days of ride-hailing operation





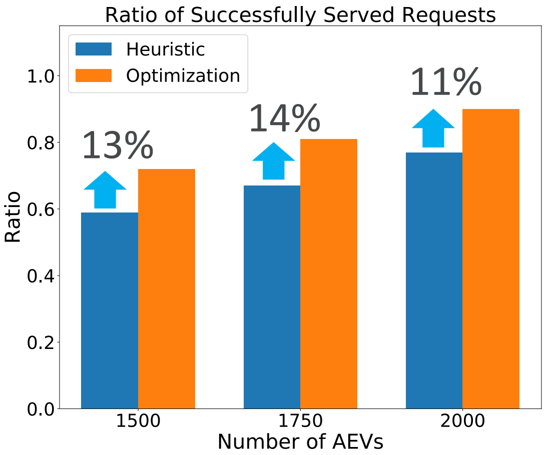


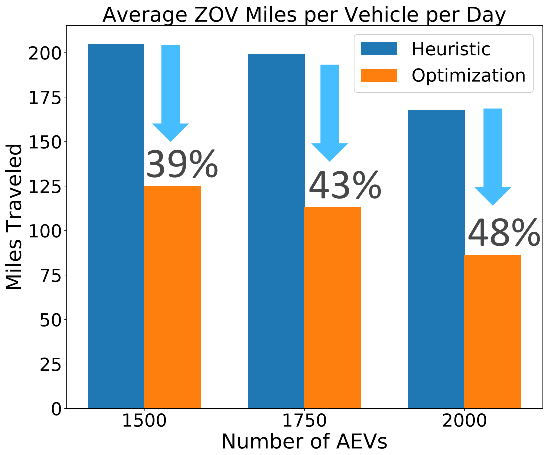


BENEFITS OF AEV FLEET OPERATION USING OPTIMIZATION APPROACH

- Optimization is most effective for a fleet size of between 1,500 and 2,000 vehicles
- For a fleet of 1,750 ride-hailing AEVs, optimization-based centralized fleet management would result in 14% more ride requests satisfied and 43% fewer zero-occupancy miles traveled than if AEVs make independent decisions based on heuristic strategy

Using today's charging station locations, assume all chargers are 50-kW



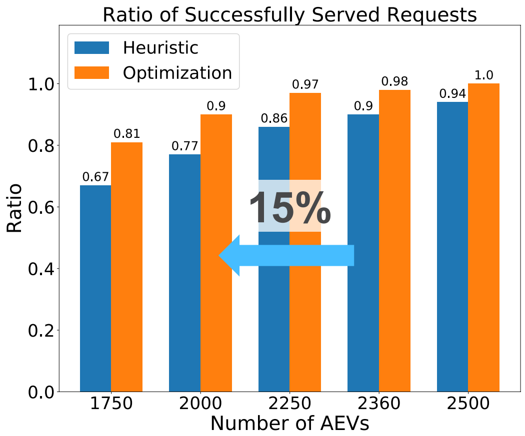


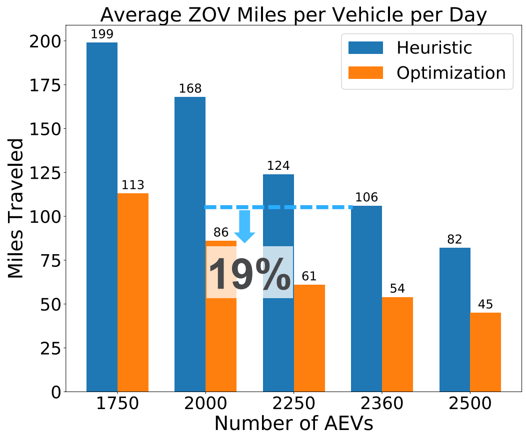
BENEFITS OF AEV FLEET OPERATION USING OPTIMIZATION APPROACH

To satisfy 90% of ride requests (i.e. ratio of 0.9):

- An AEV taxi fleet using heuristic strategy needs 2,360 vehicles
- A centrally, optimally controlled fleet needs 2,000 vehicles (15% reduction)
- The smaller, centrally controlled fleet also drives 19% fewer empty miles

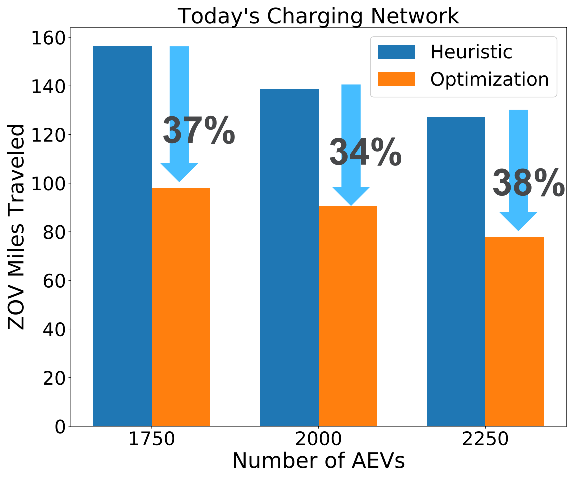
Using today's charging station locations, assume all chargers are 50-kW

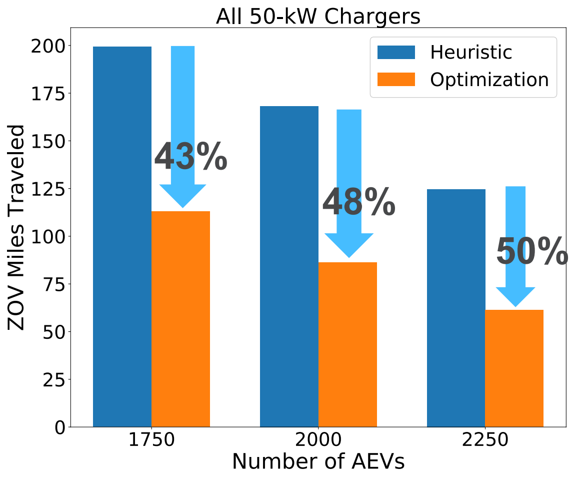




PERFORMANCE UNDER DIFFERENT CHARGING NETWORKS

- Optimization is more effective when fleet has greater access to fast charging.
- 6% - 14% greater reduction in zero occupancy vehicle miles when all chargers are 50-kW.





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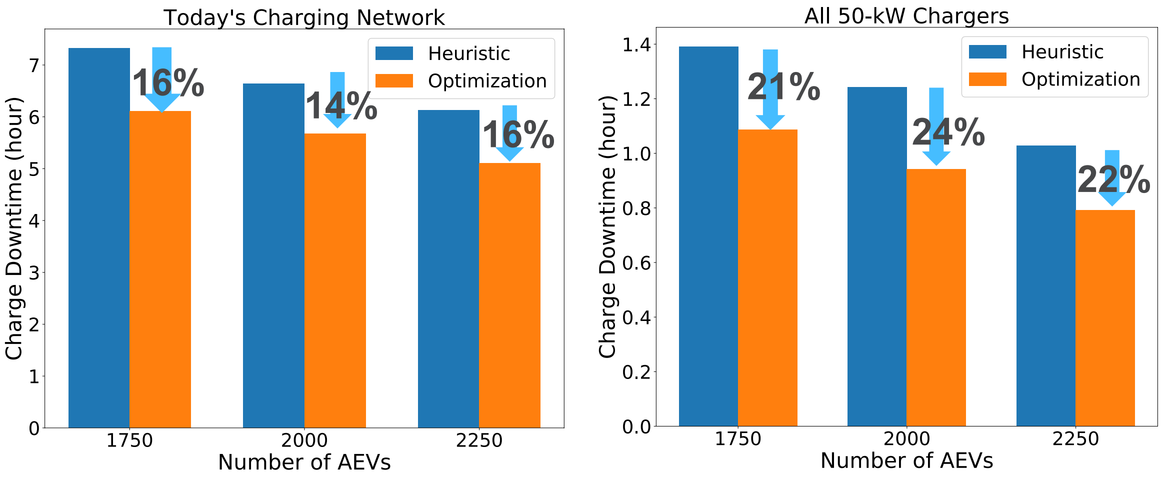
PERFORMANCE UNDER DIFFERENT CHARGING NETWORKS

- Optimization approach provides at least 14% greater reduction in charging downtime than heuristic approach
- Centrally optimized fleet can gain additional reduction in charging downtime (at least 5%) when using 50-kW charging network



RESPONSES TO PREVIOUS YEAR REVIEWER'S COMMENTS

- This project was not reviewed last year

COLLABORATION AND COORDINATION WITH OTHER INSTITUTIONS

- This project was part of the Advanced Fueling Infrastructure Pillar
- The principal investigator also participated in the project “Charging Infrastructure Design Trade-Offs For a Fleet of Human-Driven and Fully Automated Electric Vehicles in San Francisco (EEMS039)” to coordinate assumptions and methodologies

SUMMARY

- Developed a framework for integrated dispatching and charging management of an automated electric vehicle ride-hailing fleet
- A case study in New York City was conducted to investigate the benefits of systematic optimization approach comparing to a heuristic approach
- **Key findings:**
  - For a fleet of 1,750 ride-hailing AEVs to meet 100,000 daily requests in NYC, optimization-based, centralized fleet management would result in 14% more ride requests satisfied and 43% fewer zero-occupancy miles traveled than if AEVs make independent decisions based on heuristic strategy
  - Optimization approach can provide considerable reductions in both ZOV miles and charging downtime, and more benefits can be achieved when the fleet has access to faster charging network

PROPOSED FUTURE RESEARCH

The following additional research is recommended for future projects to make increasingly intelligent dispatching decisions to improve operational efficiency and increase mobility

- Dynamic intelligent algorithms should be developed that adapt to varying grid, traffic, and other conditions
- Prediction capabilities for transportation system activities will be important to enable sophisticated fleet management strategies
- Multi-stage optimization and artificial intelligence (AI) approaches should be investigated to consider both spatial and temporal dynamics of ride-hailing requests and AEV operations
- Future research should also study how to manage high-mileage electric vehicle driving and charging to maximize vehicle and battery life

Any proposed future work is subject to change based on funding levels

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MOBILITY FOR OPPORTUNITY

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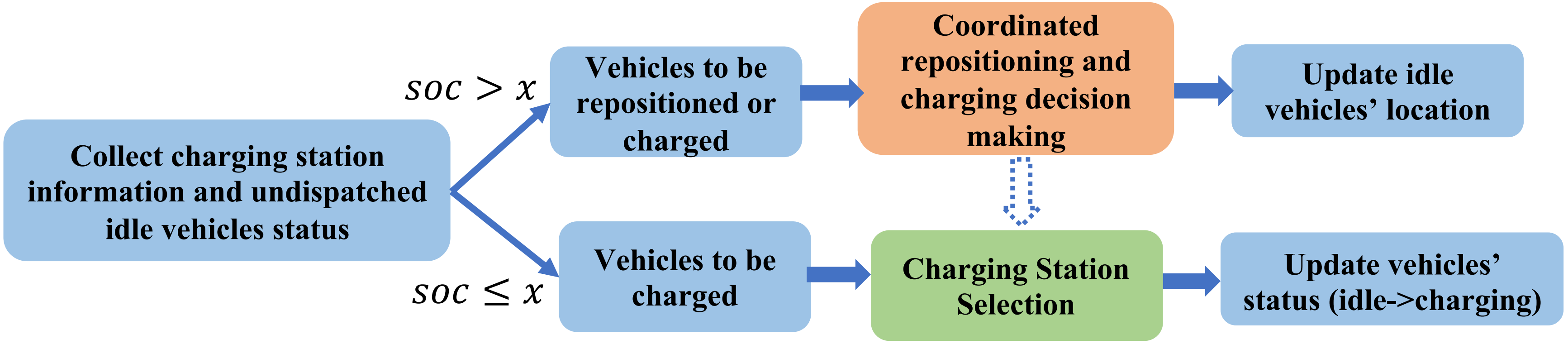
TECHNICAL BACK-UP SLIDES

APPROACH

Idle Vehicle Management



APPROACH

Agent-based Ride-Hailing Fleet Management Simulation Platform

- Simulation environment includes automated electric vehicle (AEV) agents and charging station(CS) agents.
- Both heuristic and optimization approaches are implemented.
- This platform utilizes real-world ride-hailing requests data to simulate the travel demand from riders, (i.e., New York City taxi data).

Optimization Solver + Dispatching Algorithms

- Rider Pick-up
- Repositioning
- Charging Decision Making

Simulation Environment

AEV Agents

- Basic states: location, energy state, …
- Operation Status: in-service, idle, charging, reposition, …
- Vehicle specifications: battery capacity, EV make model, …
- Vehicle charging model
- Energy consumption model
- Historical operation status
- Etc..

CS Agents

- Location
- Number of chargers
- Number of available chargers
- Waiting time
- Maximum charging power
- Historical operation status
- Etc.

Ride-Hailing Requests

NYC taxi data: Pick-up time/locations, Drop-off time/locations, etc.

TECHNICAL ACCOMPLISHMENTS

Optimization models – Reposition and charging decision making

$$\max \quad \alpha \sum_{v\in V}\sum_{r\in R_v} P_b^{vr} G_v^r + \beta \sum_{v\in V}\left(E_v - \sum_{r\in R_v} P_b^{vr} e_b^{vr} + \sum_{s\in S_v} P_c^{vs}\left(E_{cp}^v - E_v\right)\right) - \gamma \sum_{v\in V}\sum_{s\in S_v} P_c^{vs}\left(t_c^{vs} + \tau_c^{vs}\right)$$

Time cost for charging

Overall reposition rewards

AEV fleet's overall energy state

$$s.t. \quad \sum_{s\in S_v} P_c^{vs} + \sum_{r\in R_v} P_b^{vr} = 1, \qquad v\in V$$

$$\sum_{v\in V}\sum_{r\in R_v} P_b^{vr} = \min(|V|, |R|)$$

$$P_b^{vr}, P_c^{vs} \in \{0,1\}$$

Input Information

- Idle vehicle status: location/energy state/vehicle specifications
- Charging station status: location/queue wait time/charging power
- Request status: spatial distribution and priority based on wait time

Decision Output

- Charging decision making
- Repositioning/location selection

$\boldsymbol{v} \in \boldsymbol{V}$: the set of idle vehicles in the ride-hailing fleet

$\boldsymbol{r} \in \boldsymbol{R_v}$: the set of TAZs/regions that are close to vehicle v

$\boldsymbol{s} \in \boldsymbol{S_v}$: the set of charging stations that are close to vehicle v

$\boldsymbol{P_b^{vr}}$: the decision variable for repositioning

$\boldsymbol{P_c^{vs}}$: the decision variable for charging

$\boldsymbol{G_v^r}$: the reward value for vehicle v repositioning to r

$\boldsymbol{t_c^{vs}}$: charging time cost for vehicle v in charging station s

$\boldsymbol{\tau_c^{vs}}$: travel time cost for vehicle v to charging station s

$\boldsymbol{E_v}$: energy state of vehicle v

$\boldsymbol{E_{cp}^v}$: battery capacity of vehicle v

$\boldsymbol{e_b^{vz}}$: energy cost for vehicle v traveling to region z

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TECHNICAL ACCOMPLISHMENTS

Optimization models – Charging station selection

$$\min \quad \mu\Delta + \sum_{v\in V}\sum_{c\in C} x_{vc}\left[\boxed{(\tau_t^{vc} + \tau_w^c)} + \boxed{(E_{cp}^v - E_r^v)/P_c}\right]$$

Charging time cost

Overall time cost for heading to charge

$$s.t. \quad \boxed{\sum_{v\in V} x_{vc}} \le \Delta$$

Total number of vehicles sent to charging station c

$$\sum_{c\in C} x_{vc} = 1$$

$$e_t^{vc} x_{vc} \le E_r^v$$

$$x_{vc} = \{0,1\}$$

Input Information

- Status of vehicles to be charged: location/energy state/vehicle specifications
- Charging Station Status: location/queue waiting time/charging power

Decision Output

- Dispatch vehicles to the optimally selected charging station

$\boldsymbol{v \in V}$: the set of vehicles needs to be charged.

$\boldsymbol{c \in C}$: the set of available charging stations.

$\boldsymbol{x_{vc}}$: the decision variable

$\boldsymbol{\tau_t^{vc}}$: the time cost for vehicle v traveling to charging station c

$\boldsymbol{\tau_w^c}$: the waiting time for charging at charging station c

$\boldsymbol{E_{cp}^v}$: the battery capacity of vehicle v

$\boldsymbol{E_r^v}$: the remaining energy of vehicle v

$\boldsymbol{e_t^{vc}}$: the energy cost for vehicle v traveling to charging station c.

$\boldsymbol{P_c}$: the maximum charging power at charging station c

TECHNICAL ACCOMPLISHMENTS

AEV fleet operation benefits from optimization